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### Towards the Development of a Global, Satellite-based, Terrestrial Snow Mission Planning Tool

Co-authors: Sujay Kumar<sup>1</sup>, Jacqueline Le Moigne<sup>2</sup>, and Sreeja Nag<sup>2,3</sup>

1=NASA GSFC - Hydrological Sciences: 2=NASA GSFC - Software Engineering: 3=Bay Area Environmental Research Institu

#### **Bart Forman**

Assistant Professor, University of Maryland

The Deborah J. Goodings Professor of Global Sustainability

Department of Civil and Environmental Engineering

December 12<sup>th</sup>, 2017



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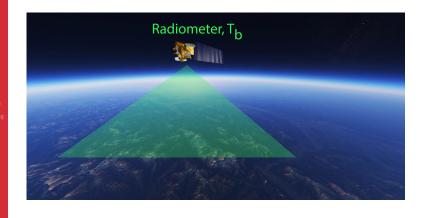
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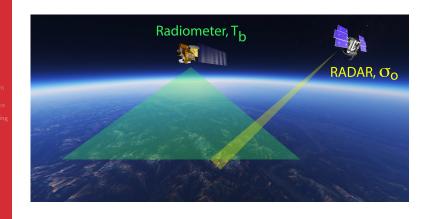
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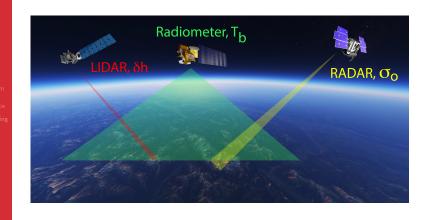
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- What observational records are needed (in space and time) to maximize terrestrial snow experimental utility?
- 2 How might observations be coordinated (in space and time) to maximize this utility?
- What is the additional utility associated with an additional observation?
- 4 How can future mission costs be minimized while ensuring Science requirements are fulfilled?



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Nature Run Snow Depth & SWE over North America
LIS + MERRA2
- model-based representation



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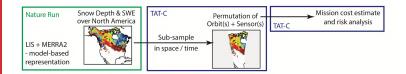
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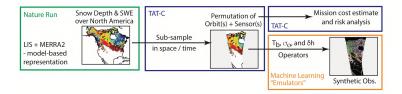
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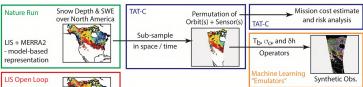
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LIS + GLDAS

- apply representative B.C. error
- no assimilation (a.k.a., Open Loop) with assimilation (merge with observations from suite of sensors)



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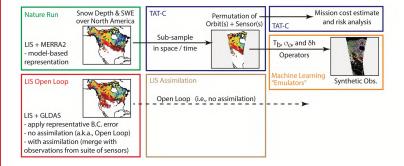
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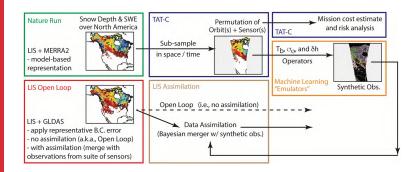
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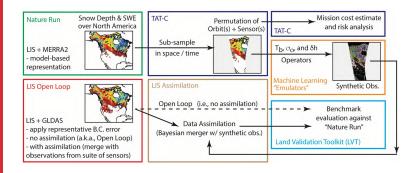
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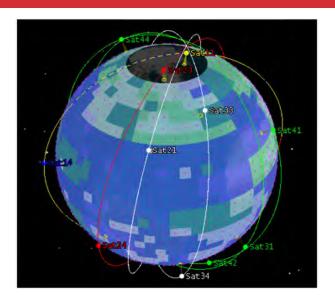
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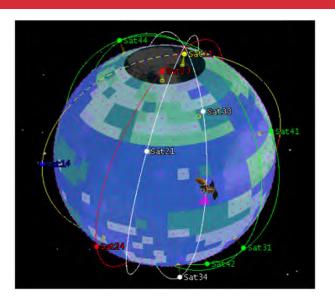
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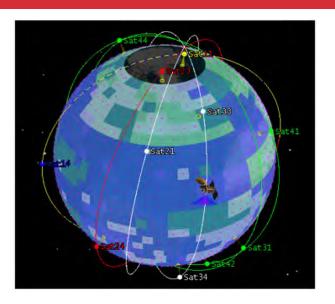
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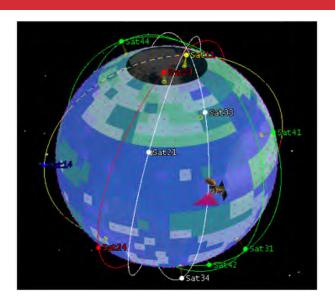
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# "Comb" Viewing $\mapsto$ Single Platform

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## "Comb" Viewing $\mapsto$ Constellation

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## Trade-off Space: Coverage vs. Resolution

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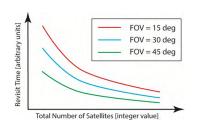
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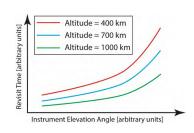
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- Explore trade-off between engineering and science
  - Field-of-View (FOV)?
  - Platform altitude?
  - Repeat cycle?
  - Single platform vs. constellation?
  - Orbital configuration(s)?
- How do we get the most scientific bang for our buck?



## Machine Learning "Emulators"

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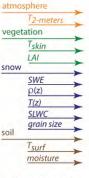
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Physically-based Land Surface Model(s)



Observation Operator (Forman et al., 2013; Forman and Reichle, 2014; Forman and Xue, 2016)



Multi-frequency, Multi-polarization Training Targets



## Machine Learning "Emulators"

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Physically-based Land Surface Model(s)



Observation Operator (Forman et al., 2013; Forman and Reichle, 2014; Forman and Xue, 2016)

| 18V - 36V |   |
|-----------|---|
| 18H - 36H |   |
| 10V - 36V |   |
| 10H - 36H | - |

Multi-frequency, Multi-polarization Training Targets



## Machine Learning "Emulators"

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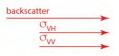
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Physically-based Land Surface Model(s)



Observation Operator (Forman et al., 2013; Forman and Reichle, 2014; Forman and Xue, 2016)



Multi-frequency, Multi-polarization **Training Targets** 



## **Spatiotemporal Variability**

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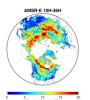
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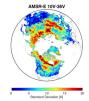
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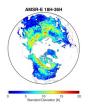
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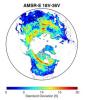
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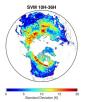
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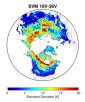


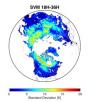


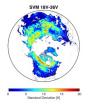














## **Spatiotemporal Variability**

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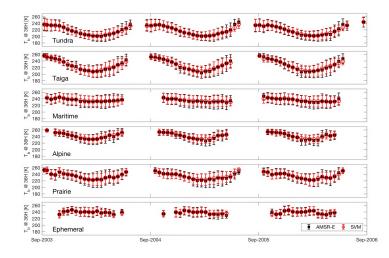
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## **Relevancy Scenarios**

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- Scenario 1: Benchmark Analysis
  - Passive MW Assimilation only
- Scenario 2: Comparative Analysis
  - ▶ Passive MW vs. Active MW vs. LIDAR
- Scenario 3: Multi-sensor Analysis
  - single-sensor platform
  - multi-sensor platform
  - constellation of sensors



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- Global snow mission will require evidence of achievable science via OSSE ... or some other means
- NASA LIS provides "nature run" plus assimilation framework
- TAT-C provides spatiotemporal sub-sampling of observations, including cost estimates and risk assessments
- Machine learning maps model state(s) into observation space (i.e.,  $T_b$  and  $\sigma_0$ )
  - ▶ Enables integration of  $T_b$ ,  $\sigma_0$ , and  $\delta h$  in geophysical realm (i.e SWF and show depth)
  - Multiple frequencies/polarizations/observations allow for flexibility and modularity in DA framework
- Snow OSSE is on-going → open to ideas + suggestions!



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## Thank You.

# **Questions and/or Comments?**

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NASA New Investigator Program (NNX14AI49G) NASA GRACE-FO Science Team (NNX16AF17G) NASA High Mountain Asia Science Team (NNX17AC15G)



High-performance computing support provided by UMD's Division of Information Technology



## SVM Mathematical Framework (1 of 2)

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For parameters C>0 and  $\varepsilon>0$ , the **standard (primal)** form is:

$$\begin{aligned} & \underset{\mathbf{w}, \, \delta, \, \boldsymbol{\xi}, \, \boldsymbol{\xi}^*}{\text{minimize}} & & \frac{1}{2} \langle \mathbf{w} \cdot \mathbf{w} \rangle + C \sum_{i=1}^m \left( \xi_i + \xi_i^* \right) \\ & \text{subject to} & & \langle \mathbf{w} \cdot \phi(\mathbf{x}_i) \rangle + \delta - z_i \leq \varepsilon + \xi_i \\ & & z_i - \langle \mathbf{w} \cdot \phi(\mathbf{x}_i) \rangle - \delta \leq \varepsilon + \xi_i^* \\ & & \xi_i, \xi_i^* \geq 0, i = 1, 2, \dots, m. \end{aligned}$$

where m is the available number of  $T_b$  measurements in time (for a given location in space),  $z_i$  is a  $T_b$  measurement at time i, and  $\xi$  and  $\xi^*$  are slack variables.



## SVM Mathematical Framework (2 of 2)

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Primal optimization is commonly solved in **dual form** as:

$$\begin{split} & \underset{\alpha_i, \ \alpha_i^*}{\text{minimize}} & \quad \frac{1}{2} \sum_{i,j=1}^m \left(\alpha_i - \alpha_i^*\right) \left(\alpha_j - \alpha_j^*\right) \left\langle \phi(\mathbf{x}_i) \cdot \phi(\mathbf{x}_j) \right\rangle \\ & \quad + \varepsilon \sum_{i=1}^m \left(\alpha_i + \alpha_i^*\right) - \sum_{i=1}^m z_i \left(\alpha_i - \alpha_i^*\right) \\ & \quad \text{subject to} & \quad \sum_{i=1}^m \left(\alpha_i - \alpha_i^*\right) = 0, \\ & \quad \alpha_i \ , \ \alpha_i^* \in [0 \ , \ C] \ , \ i = 1, 2, \dots, m \end{split}$$

where  $\alpha_i$  and  $\alpha_i^*$  are Lagrangian multipliers,  $\langle \phi(\mathbf{x}_i) \cdot \phi(\mathbf{x}_j) \rangle$  is the inner dot product of  $\phi(\mathbf{x}_i)$  and  $\phi(\mathbf{x}_j)$ ,  $\varepsilon$  is the specified error tolerance, and C is a positive constant that dictates a penalized loss during training.